

# A meta-analysis of technology use and cognitive aging

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The first generation who engaged with digital technologies has reached the age where risks of dementia emerge. Has technological exposure helped or harmed cognition in digital pioneers? The digital dementia hypothesis predicts that a lifetime of technology exposure worsens cognitive abilities. An alternative hypothesis is that such exposures lead to technological reserve, wherein digital technologies promote behaviours that preserve cognition. We tested these hypotheses in a meta-analysis and systematic review of studies published in Medline, PsycInfo, CINAHL, Science Direct, Scopus, Cochrane Library, ProQuest and Web of Science. Studies were included if they were observational or cohort studies focused on general digital technology use in older adults (over age 50) and included either a cognitive or dementia diagnosis outcome. We identified 136 papers that met inclusion criteria, of which 57 were compatible with odds ratio or hazard ratio meta-analysis. These studies included 411,430 adults (baseline age  $M = 68.7$  years; 53.5% female) from cross-sectional and longitudinal observational studies (range: 1–18 years,  $M = 6.2$  years). Use of digital technologies was associated with reduced risk of cognitive impairment ( $OR = 0.42$ , 95% CI 0.35–0.52) and reduced time-dependent rates of cognitive decline ( $HR = 0.74$ , 95% CI 0.66–0.84). Effects remained significant when accounting for demographic, socioeconomic, health and cognitive reserve proxies. All studies were evaluated for quality on the basis of a standardized checklist; the primary outcomes replicated when limiting analyses to the highest-quality studies. Additional work is needed to test bidirectional causal interpretations, understand mechanisms that underpin technological reserve, and identify how types and timings of technology exposures influence cognitive health.

When it comes to cognitive aging, biology is not destiny. Some older adults show robust cognitive functioning well into older age, even in the face of widespread neuropathological changes<sup>1,2</sup>. This resiliency against neuropathological processes in older adulthood has given rise to cognitive reserve theory<sup>3</sup>, which contends that exposure to complex mental activities leads to better cognitive well-being in older age. Complex mental activities are typically measured by variables such as years of education, frequency of social interactions and engagement with

cognitively demanding leisure activities (for example, reading, crossword puzzles)—some of which have been part of the human experience for centuries if not longer. Today's older adults, however, represent the first cohort to have navigated a fundamental shift in the cognitive landscape: prolonged exposure to digital technologies.

The impact of the digital revolution on daily life is so pervasive that comparisons and contrasts to 'the good ole days' have become cliché. However, when one considers the cognitive experience of an

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individual born in the aftermath of World War II, the changes are stunning. Someone born in 1945 would have entered adulthood in a world where commerce was conducted by paper currency and checks, new knowledge was acquired by physically searching through stacks of encyclopaedias, prospective remembering required memory processes to be self-initiated, navigation to new areas required paper maps, and letters were written by hand and sent via post, with days to weeks in latencies between responses<sup>4</sup>. This same individual is now approaching their 80's and lives in a world where shopping occurs on the internet with credit cards, new knowledge is acquired by typing a question into a search engine, prospective memory is supported by digital calendars with automatic reminders, navigation is facilitated by GPS devices that are installed in most cars (or phones), and text- or video-based communications can occur instantaneously with people across the world. What is the cognitive impact of such dramatic changes in the environment?

One possible answer is that people's natural, everyday uses of digital technologies weaken their cognitive abilities across the lifespan. This concern arises in part from studies that linked passive screen time to weaker cognitive abilities, mostly in children and adolescents<sup>5–8</sup>. In addition, increased dependence on technology for maintaining semantic knowledge (that is, the 'Google effect'), autobiographical memories<sup>10</sup>, spatial memory<sup>11</sup> and prospective memory planning<sup>12</sup> might accelerate cognitive decline if such cognitive offloading<sup>13</sup> decreases the amount of practice/engagement with one's own intrinsic cognitive abilities (see ref. 14 for conceptual elaboration and evaluation). Furthermore, given that older adults are at greater risk for cognitive control difficulties<sup>15,16</sup>, device-driven distractions could hypothetically worsen the real-world impacts of normal age-related cognitive deficits<sup>17–20</sup>. According to the digital dementia hypothesis<sup>21–23</sup>, the interaction among these three factors—passive screen time, offloading of cognitive abilities onto devices and susceptibility to distractions—should increase rates of dementia in older adults, especially those with greater lifetime exposures to these technologies.

A different viewpoint is that exposures to digital technologies can protect against cognitive decline (technological reserve hypothesis). Stern and colleagues<sup>24</sup> defined reserve as 'a property of the brain that allows for cognitive performance that is better than expected given the degree of life-course-related brain changes and brain injury or disease'. The technological reserve hypothesis builds on this definition by specifying that a technology-enriched environment can facilitate reserve through several pathways including increasing complex mental activities, social connection and digital compensation/scaffolding<sup>25,26</sup>. According to the technological reserve hypothesis, greater digital engagement should be associated with a net benefit to cognitive and functional outcomes, relative to expectations based on age, brain injury or disease.

Several lines of evidence have emerged that support the technological reserve hypothesis. For example, while early studies found that older adults showed considerable difficulty learning new technologies<sup>27</sup> more recent studies have shown that older adults with a range of cognitive abilities are capable of learning to use modern commercially available digital technologies<sup>28,29</sup>. This ability to learn new technologies in older adulthood was particularly highlighted during the COVID-19 pandemic when video calling and virtual meetings were widely adopted among older adults<sup>30</sup>, behaviours that in and of themselves can broaden and reinforce social connection<sup>31,32</sup>, minimizing mental health impacts that can contribute to cognitive decline<sup>33</sup>. Furthermore, digital leisure activities such as computerized gaming have increased in older adults and such activities seem to be associated with benefits rather than harms to cognition in later life<sup>34</sup>. Finally, developing evidence shows that cognitive offloading to digital devices can allow older adults to compensate for age-related declines in cognitive control, memory and navigation abilities, increasing functional performance even in the face of cognitive decline<sup>35</sup>. In integrating these broad literatures, older

adults who had greater lifetime engagement with digital technologies may on average show better cognitive well-being, operationalized as better cognitive test performance and lower rates of dementia in older age.

Epidemiological trends have suggested that cognitive decline and incident dementia rates have decreased since the 1990s in both the United States and Europe<sup>36,37</sup>. This is an interesting trend because this time period corresponds to internet commercialization and the proliferation of home computing. Yet, there has been limited work to attempt to quantitatively dissociate the digital dementia and technology reserve viewpoints, in part because understanding technology's influence on cognition over time is inherently challenging. For example, digital exposures have differed across countries, age groups, education levels, occupations and socioeconomic status levels, factors that have led to a 'digital divide'<sup>38,39</sup>. Even though this divide has been narrowing in recent years<sup>40,41</sup>, its existence has implications for understanding the cognitive impact of technology use because sample characteristics, such as the age of the population studied and wealth disparities across countries, are both associated with lower technology exposure on average<sup>38</sup> and increased risk for developing dementia<sup>42</sup>. Therefore, determining whether natural exposures to digital technologies is associated with cognitive functioning requires accounting for such sample factors. Another general challenge is that the design of individual studies could potentially bias interpretations of technology's impact on cognition if the sample is non-representative or if the design relies on online surveys and tablet- or computer-based data collection<sup>43</sup>; these approaches could systematically exclude older adults who have not crossed the digital divide. Evaluating the impact of study design characteristics is thus necessary for contrasting theoretical viewpoints in the literature.

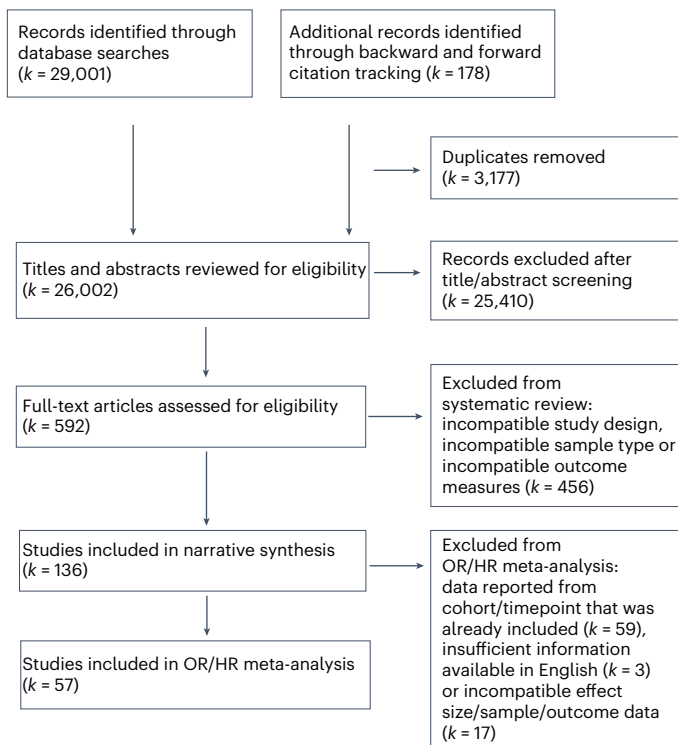
In the current study, we employed a meta-analytic framework to investigate whether general/natural engagement with everyday digital technologies was cross-sectionally and longitudinally associated with worse or better cognition in middle-aged and older adults. We tested whether outcomes were moderated by sample or study design characteristics. Furthermore, we investigated whether the influence of technology exposure might be attributed to non-causal factors by examining whether adjusting for education, occupation, an active lifestyle, social support, socioeconomic factors or health/co-morbidities weakened the association between cognition and technology use.

## Results

### Study search results

Figure 1 illustrates the study search results. Titles and abstracts were screened in eight databases: Medline (through PubMed), PsycInfo, CINAHL, Science Direct, Scopus, Cochrane Library, ProQuest and Web of Science. These databases were searched for published observational and cohort studies on cognition in relation to natural uses of digital technologies in middle-aged and older adults ( $\geq 50$  years at baseline). The age range ( $\geq 50$  years) was selected because middle-aged adults in this literature would still constitute 'digital pioneer' adults who did not have internet access during childhood. Furthermore, in longitudinal studies, some of these middle-aged individuals would have crossed into traditional 'older adulthood' cut-offs ( $\geq 65$  years) at their follow-up timepoints.

During title and abstract screening ( $k = 26,002$ ) and full-text screening ( $k = 592$ ), we excluded case studies, studies that combined computer usage with standard household technology usage (for example, microwaves, televisions), studies focused on specific digital performance metrics (for example, keystroke speed, mouse movements), studies focused on researcher-developed apps and digital-based interventions (for example, computerized cognitive training, video game training, mobile fitness, eHealth delivery and digital psychoeducation<sup>34,44–52</sup>) because these study types do not provide unambiguous tests of the digital dementia hypothesis. Such digital intervention studies focus on training older adults to engage in uses of



**Fig. 1 | Flowchart of search methodology.** Depiction of study identification and selection process.

digital technology that are already known to be beneficial in non-digital formats (for example, physical exercise, cognitive training, healthcare access); these approaches are therefore incongruent with testing the digital dementia hypothesis, which contends that people's natural uses of computer, smartphone and internet-based technologies increase rates of cognitive decline.

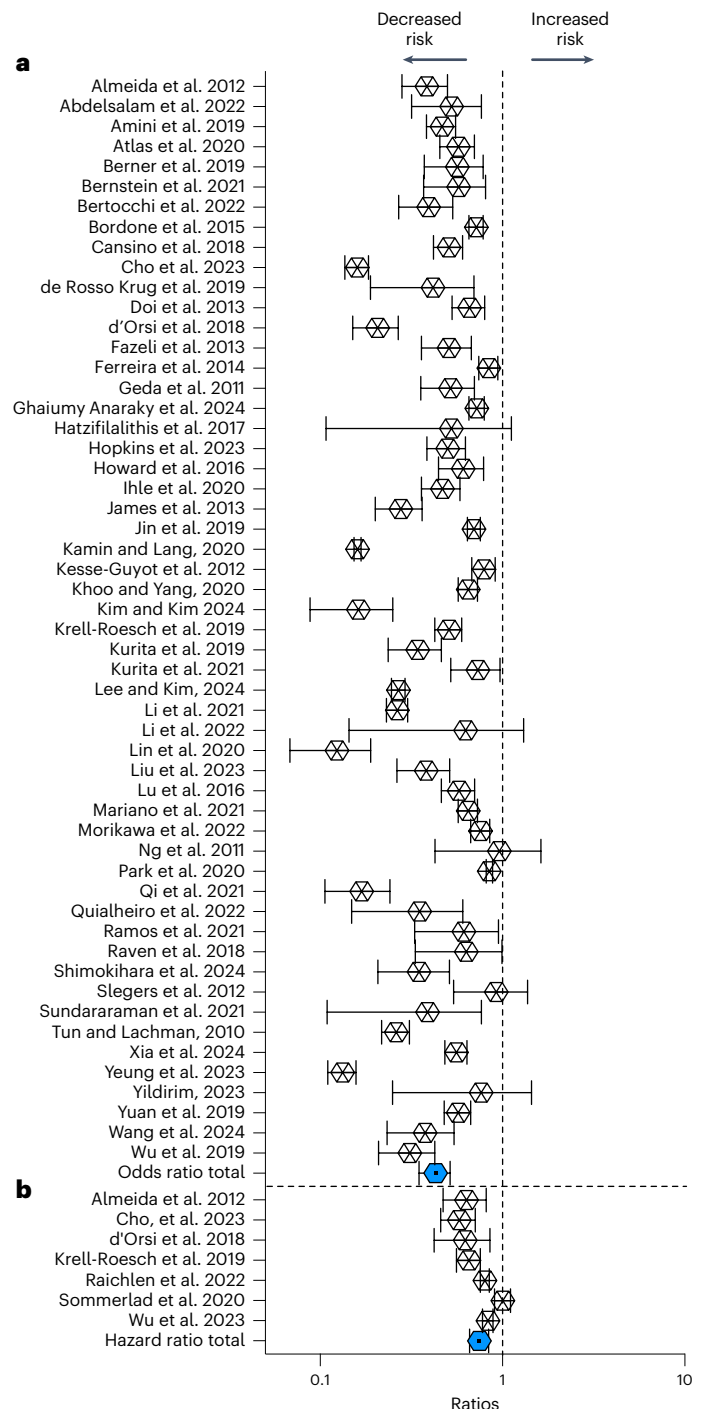
The search process yielded 136 full-text articles that met inclusion criteria<sup>53–188</sup>. Supplementary Table 1 details the 79 studies that were included in the systematic review but not the meta-analysis due to reporting data from the same cohort/timepoint as other included studies ( $k = 59$ ), not reporting complete analyses in English ( $k = 3$ ), or reporting variables, samples or effect sizes in a manner that was statistically incompatible with odds ratio (OR) or hazard ratio (HR) meta-analysis approaches ( $k = 17$ ).

The final OR/HR meta-analytic sample of 57 studies included 411,430 middle-aged or older adults with an average age of 68.7 years at baseline assessment. Approximately half of participants were female (53.5%). Twenty studies employed a longitudinal design, with an average duration of 6.2 years (s.d. = 4.0). The primary endpoint was dementia or mild cognitive impairment (MCI) diagnosis in 26.3% of studies and cognitive testing in 73.7% of studies (see Supplementary Table 2 for detailed study characteristics including cognitive endpoints, demographics and covariates).

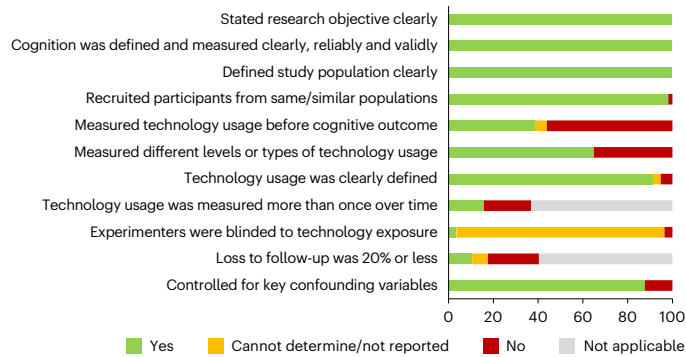
### Association of technology use with cognitive outcomes

We extracted the maximally covariate-adjusted effect sizes from studies whenever possible (for all individual study covariates and notes on effect size conversions, see Supplementary Table 2). Greater use of everyday digital technologies was associated with reduced odds for cognitive decline, operationalized as lower cognitive test scores and reduced MCI or dementia diagnoses (pooled OR = 0.42,  $P < .0001$ , 95% CI 0.349–0.516,  $k = 54$ ; Fig. 2a). The subsample of studies that reported HRs—a metric of time-dependent rates in longitudinal studies—similarly found that technology use was associated with decreased rates of cognitive decline (pooled HR = 0.74,  $P < .0001$ , 95% CI 0.66–0.84,

$k = 7$ ; Fig. 2b). Across both the OR and HR meta-analyses, 51 of the 57 studies had 95% confidence intervals that indicated technology usage was associated with significantly decreased risk for cognitive impairment. Similarly, among the papers in the supplementary section, 71 of the 79 studies reported that technology usage was associated with reduced risk for cognitive impairment following covariate adjustment (Supplementary Table 1). None of the 136 papers that were systematically reviewed reported that technology use increased risk for cognitive



**Fig. 2 | Forest plot of studies included in the meta-analysis. a, b,** Odds ratio forest plots ( $k = 54$ ) (a) and hazard ratio forest plots ( $k = 7$ ) (b) of the relationship between technology usage and the cognitive-outcome variable. Ratios are plotted on a  $\log_{10}$  scale, with values lower than 1.0 indicating that technology usage was associated with protection against cognitive decline (decreased risk). Error bars reflect 95% confidence intervals.



**Fig. 3 | Study quality ratings.** Structured ratings of study quality using a modified version of the observational and cohort cross-sectional quality assessment tool from the National Heart, Lung and Blood Institute.

impairment in middle-aged or older-aged adults. Risk for publication bias was minimal (Supplementary Figs. 1 and 2).

In terms of type of technology assessed, computer use ( $k = 18$ ,  $OR = 0.536$ ,  $P < 0.0001$ , 95% CI 0.456–0.630), internet use ( $k = 23$ ,  $OR = 0.416$ ,  $P < 0.0001$ , 95% CI 0.295–0.588), smartphone use ( $k = 11$ ,  $OR = 0.514$ ,  $P < 0.001$ , 95% CI 0.428–0.618) and mixed/multiple uses of digital technologies ( $k = 7$ ,  $OR = 0.252$ ,  $P < 0.001$ , 95% CI 0.167–0.380) were each associated with reduced risk of cognitive impairment (Supplementary Fig. 3). The three meta-analysed studies on social media use in older adults showed inconsistent findings for cognitive outcomes ( $OR = 0.384$ ,  $P = 0.069$ , 95% CI 0.137–1.08). In terms of longitudinal and cross-sectional designs, the association between technology use and reduced cognitive decline was observed for both longitudinal studies ( $k = 17$ ,  $OR = 0.461$ ,  $P < 0.001$ , 95% CI 0.307–0.692) and cross-sectional studies ( $k = 37$ ,  $OR = 0.410$ ,  $P < 0.0001$ , 95% CI 0.342–0.493; measure of heterogeneity:  $Q = 0.27$ ,  $P = 0.606$ ; Supplementary Fig. 4).

Figure 3 indicates that an average of 72.6% (s.d. = 9.4%) of rated study quality features were observed in the meta-analysed literature (National Heart, Lung and Blood Institute (NHLBI) rating tool). The majority of the studies included controlling for confounding variables in reported outcomes, employing a validated measure of cognition and measuring different types or levels of technology usage. Some weaknesses in the literature were also identified, including that few studies blinded experimenters to the technology or cognitive-outcome data, studies often only measured technology usage once and studies had moderate attrition at follow-up.

### Results of meta-regression and sensitivity analyses

Of the 57 meta-analysed studies, all but three<sup>78,80,103</sup> provided information necessary to calculate OR effect sizes, which were used for meta-regression analyses. Table 1 (Model 1) demonstrates that sample characteristics, including sample size, country-level income (defined by World Bank classifications), gender and age, were not significantly associated with effect sizes (Supplementary Fig. 5). In follow-up analyses, we examined whether effects were driven by studies that included a large proportion of middle-aged adults; strong effect sizes were still observed in the 38 studies that had an average baseline age  $\geq 65$  years old ( $OR = 0.41$ ,  $P < 0.0001$ , 95% CI 0.31–0.53) as well as the 16 studies that had an average age between 50 and 65 years old ( $OR = 0.46$ ,  $P < 0.0001$ , 95% CI 0.36–0.59).

Table 1 also shows the meta-regression on study design characteristics (Model 2). Effect sizes were not significantly moderated by the type of cognitive-outcome measure (diagnosis or cognitive test), the type of sampling methodology (representative probability sampling versus convenience sampling), study quality ratings, year of data collection, or whether the study was conducted entirely face to face versus required some technology usage for data acquisition

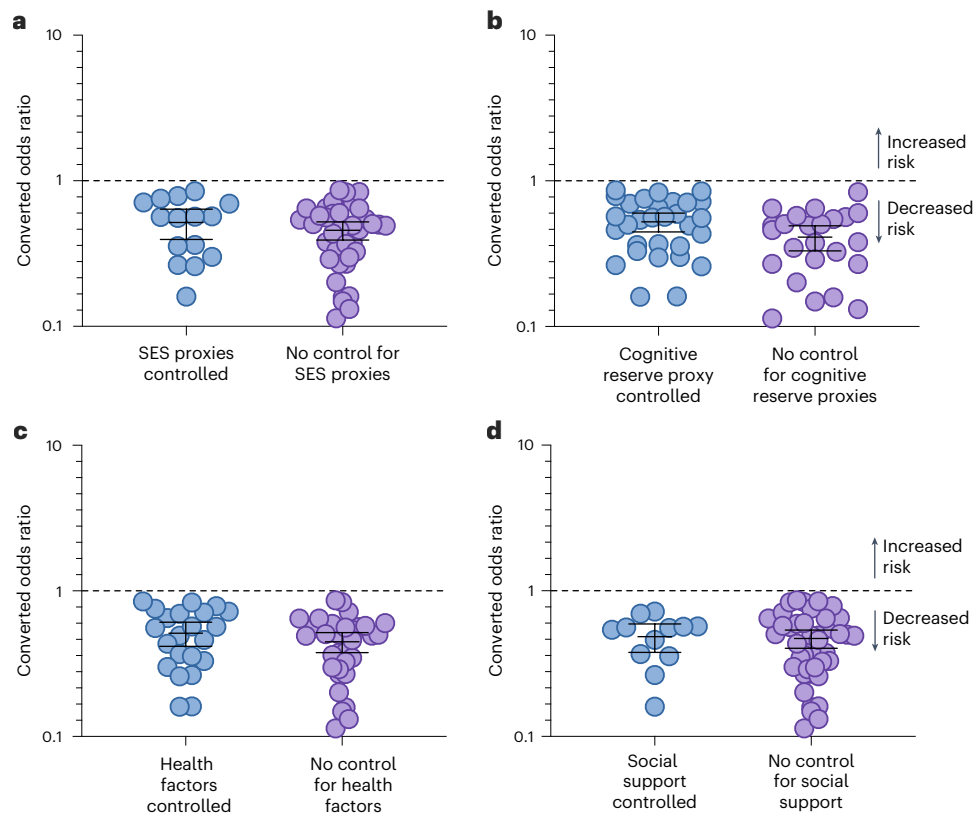
**Table 1 | Meta-regressions of odds ratio converted effect sizes in relation to sample characteristics (Model 1), study characteristics (Model 2) and conceptual factors (Model 3)**

Effect	Estimate	s.e.	95% CI		Z-value	P
			LL	UL		
<b>Model 1: sample characteristics</b>						
Intercept	0.20	0.75	-1.27	1.66	0.26	0.79
Baseline age	<0.01	0.01	-0.03	0.01	-0.86	0.39
Percent female	-0.01	0.01	-0.02	0.01	-1.04	0.30
N of sample <sup>a</sup>	<0.01	<0.01	<0.01	<0.01	-1.55	0.12
Lower-middle country income	-0.06	0.39	-0.82	0.70	-0.15	0.88
Upper- middle country income	-0.15	0.19	-0.51	0.22	-0.79	0.43
Model 1 test: $Q = 4.94$ , d.f. = 5, $P = 0.42$						
<b>Model 2: study characteristics</b>						
Intercept	36.24	34.93	-32.22	104.70	1.04	0.30
Year data collection began	-0.02	0.01	-0.05	0.02	-1.08	0.28
Study quality proportion	0.43	1.23	-1.99	2.85	0.35	0.73
Outcome was a diagnosis	-0.16	0.47	-1.08	0.76	-0.34	0.74
Study used probability sampling	-0.14	0.22	-0.57	0.30	-0.61	0.54
Technology used during data collection	-0.03	0.22	-0.46	0.40	-0.15	0.88
Model 2 test: $Q = 3.81$ , d.f. = 5, $P = 0.70$						
<b>Model 3: conceptual factors</b>						
Intercept	-1.02	0.14	-1.28	-0.75	-7.51	<0.01
Adjusted for socioeconomic factors	0.08	0.24	-0.40	0.57	0.34	0.74
Adjusted for cognitive reserve factors	0.39	0.28	-0.15	0.94	1.43	0.15
Adjusted for health factors	-0.16	0.30	-0.75	0.43	-0.53	0.60
Adjusted for social factors	-0.08	0.25	-0.57	0.40	-0.34	0.73
Model 3 test: $Q = 2.85$ , d.f. = 4, $P = 0.58$						

Analyses were two-tailed, without correction for multiple comparisons. Note: number of studies with odds ratio effect sizes, 54; CI, confidence interval; LL, lower limit; UL, upper limit. <sup>a</sup>Coefficient and upper/lower limits rounded to zero because of large sample sizes.

(for example, online questionnaire, in-person tablet responses; Supplementary Figs. 6–8).

Conceptually, technology use might be a proxy for socioeconomic status, engagement in other cognitively engaging activities, overall health behaviours and/or greater social support. If the association between technology use and cognition was strictly a manifestation of one of these four constructs, then the studies that adjusted for such factors should show null effect sizes, or at least reduced effect sizes. However, a meta-regression indicated that adjustment for socioeconomic factors, cognitive reserve proxies, health factors and social support did not significantly predict variance in the effect sizes (Table 1, Model 3). Figure 4 demonstrates that technology use was associated with better cognition in the studies that adjusted for socioeconomic factors ( $k = 15$ ,  $OR = 0.483$ ,  $P < 0.0001$ , 95% CI 0.389–0.603), cognitive reserve



**Fig. 4 | Effect sizes as a function of potential moderators. a–d.** Derived effect sizes in relation to whether the converted effect size was adjusted for (a) socioeconomic status (SES) proxies ( $k = 15$  adjusted,  $k = 39$  not adjusted); (b) cognitive reserve proxies ( $k = 30$  adjusted,  $k = 24$  not adjusted); (c) health and

co-morbidities ( $k = 22$  adjusted,  $k = 32$  not adjusted); and (d) social support variables ( $k = 12$  adjusted,  $k = 42$  not adjusted). Odds ratios are plotted on a  $\log_{10}$  scale. The centre bar indicates the mean value and the error bars reflect 95% confidence intervals.

proxies ( $k = 30$ ; OR = 0.479,  $P < 0.0001$ , 95% CI 0.361–0.635), health factors ( $k = 22$ , OR = 0.462,  $P < 0.0001$ , 95% CI 0.327–0.652) and social support ( $k = 12$ , OR = 0.458,  $P < 0.0001$ , 95% CI 0.365–0.575). We further confirmed that technology use was still predictive of better cognition in studies that controlled for education (OR = 0.488,  $P < 0.0001$ , 95% CI 0.368–0.648), studies that controlled for occupation (OR = 0.469,  $P < 0.001$ , 95% CI 0.306–0.721) and studies that controlled for reading, playing games/puzzles, or similar lifestyle activities (OR = 0.492,  $P = 0.016$ , 95% CI 0.276–0.878).

A final set of analyses was conducted to evaluate the combined impact of key covariates and features of a strong study design. For this analysis, we included only the studies that used probability sampling methodologies and controlled for age, gender and education. We observed similar, large effect sizes among this subset of studies for both OR analyses ( $k = 18$ , OR = 0.442,  $P < 0.001$ , 95% CI 0.299–0.654) and HR analyses ( $k = 4$ , HR = 0.62,  $P < 0.001$ , 95% CI 0.56–0.69). When further restricting analyses to those with NHLBI study quality ratings greater than 70%, we continued to observe large effect sizes for OR analyses ( $k = 15$ , OR = 0.459,  $P < 0.001$ , 95% CI 0.296–0.711) and HR analyses ( $k = 3$ , HR = 0.62,  $P < 0.001$ , 95% CI 0.55–0.70).

## Discussion

Technology engagement was associated with reduced odds of cognitive decline in middle-aged and older adults. There was no credible evidence from the longitudinal studies, or the meta-analysis as a whole, for widespread digital ‘brain drain’<sup>22</sup> or ‘digital dementia’<sup>21,23</sup> as a result of general, natural uses of digital technology. The magnitude of the association between technological engagement and positive cognitive outcomes (95% CI 0.35–0.52) was similar to or stronger than several previously documented protective factors for dementia such as

blood pressure reduction (OR = 0.87)<sup>189</sup>, physical activity (OR = 0.65)<sup>190</sup>, increasing years of education (ORs = 0.38–0.53)<sup>191</sup> and other cognitively stimulating leisure activities (OR = 0.69)<sup>192</sup>. In the following sections, we consider both non-causal and causal explanations for technology–cognition associations, processes through which technology may facilitate reserve, and limitations that should be addressed in the coming years to advance theory and practical applications.

There are potential non-causal explanations for why frequent technology exposure would be associated with better cognitive functioning. Previous work has indicated that younger people, those with higher incomes and those with more years of education are more likely to engage with digital technologies<sup>38</sup>, and these same factors are associated with better cognitive outcomes<sup>42</sup>. In addition to demographic considerations, adoption of emerging technologies has been related to perceived usefulness, perceived ease of use, self-efficacy, existing skills, occupational experience, physical health, social support, mentally active lifestyles, contextual influences and potentially other factors that could be independently associated with preserved cognitive abilities<sup>75,193–195</sup>. Further, as with any literature, one must be cautious not to draw strong conclusions if the quality of the individual studies is low or if there is evidence of substantial publication bias.

To these ends, our systematic review and meta-analysis suggest that the technology–cognition association is unlikely to be explained solely by non-causal factors. Regarding demographic or lifestyle confounders, ~90% of the studies evaluated in the systematic review statistically controlled for variables such as age and education. Likewise, many individual studies in the OR meta-analysis controlled for socioeconomic status proxies (27.7%), cognitive reserve proxies (55.6%), social support proxies (22.2%) and/or co-morbidities/physical health

proxies (40.7%). We did not observe credible evidence for moderation of effect sizes in relation to controlling for such proxies.

With regard to methodological rigour in the reviewed studies, although there was some variability in the quality of studies (as there is for any literature), many studies included large sample sizes (median  $N = 2,579$ ), controlled for several potential confounding variables (median = 7 variables controlled), used representative sampling methodologies (52.6% of studies) and avoided requiring technology for study enrolment/completion (70.2% of studies were solely face-to-face)<sup>196</sup>. Publication bias appeared minimal and the strength of effect sizes persisted when limiting to studies that met several quality metrics (probability sampling, control of key covariates and high quality rating scores). Therefore, while the correlational designs in this literature cannot eliminate non-causal explanations, such accounts seem unlikely to solely explain technology–cognition relationships.

If non-causal factors are unlikely to be the sole explanation for technology–cognition associations, then the following questions must be considered: (1) does better cognition increase technology use with age, (2) does technology use foster better cognitive outcomes or (3) do both occur<sup>84</sup>? There is certainly evidence in the literature that better cognitive functioning—especially intelligence and executive functioning—influences rates of technology adoption and abandonment, particularly if the technology is difficult to learn or perceived as not useful<sup>29,57,80,143,144,197–201</sup>. This general pattern is the foundation for work on digital biomarkers<sup>202,203</sup> in which in-home digital monitoring<sup>166,202</sup>, smartphone use metrics<sup>154,204</sup> and online financial activities<sup>205</sup> are being used to predict risk for cognitive decline. Although correlational studies form the basis for this cognition→technology use interpretation of the literature, it nevertheless seems reasonable to infer that people with lower cognitive abilities will have more difficulty in learning new digital tasks (or analogue tasks) than people with moderate to high cognitive abilities<sup>206</sup>.

Nevertheless, the reverse direction also merits consideration: technology engagement may facilitate behaviours and mental processes that afford some protection against cognitive decline. Support for this interpretation emanates from several of the study designs covered in this literature review: 20 of the analysed studies used longitudinal designs in which technology exposure at baseline strongly predicted a cognitive outcome an average of 6 years later (OR = 0.46). Nearly all the longitudinal studies in this literature (95%) controlled for education at baseline. The longitudinal studies have also controlled for cognitive test measures at baseline (60% of studies<sup>54,56–59,62,63,65,74,79,119</sup>), excluded participants from enrolment or analyses if they had MCI or dementia at baseline (55% of studies<sup>56,57,59,61,65,67,68,71,73,74,77,79</sup>), or even conducted sensitivity analyses after excluding individuals who developed MCI or dementia within the first 1–5 years of the study period (25% of studies<sup>54,57,78,80</sup>). Technology use continued to predict better future cognitive outcomes even after these adjustments.

A bidirectional interpretation of technology exposure and cognitive functioning may best explain the collective literature. For example, in a large, nationally representative sample (Health and Retirement Study), Choi and colleagues<sup>84</sup> modelled the relationship between cognition and internet use over 4 years using cross-lagged analytical approaches<sup>152,179</sup>. These models included autoregressive factors and found that cognition at time 1 was independently associated with technology use at time 2, but also that technology use at time 1 was independently associated with cognition at time 2—thus, a bidirectional relationship.

Such bidirectional relationships are common across the dementia prevention literature. For example, decreased walking speed presages cognitive decline in a host of neurodegenerative diseases<sup>207</sup>, but the reverse causal direction is also present: regular walking leads to better cognitive performance and slower rates of cognitive decline<sup>208</sup>. Whether such bidirectional influences occur simultaneously versus serially/cyclically is unknown and requires further investigation.

### Possible factors contributing to technological reserve

The technological reserve hypothesis postulates that engagement with digital technologies promotes better cognitive outcomes than would be expected on the basis of someone's age, brain injury or disease stage. There are at least three possible pathways that could link digital engagement to better cognition: cognitively complex stimulation, social connection and compensatory behaviours. Engaging in cognitively complex activities has long been recognized to lead to better cognitive outcomes<sup>137</sup> with age, a notion which is at the core of reserve theories<sup>2,119</sup>. We identified 21 articles<sup>66,71,76,80,81,86,88,89,92,94,95,97,98,103,147,149,152,153,168,172</sup> in this literature that compared technology use to other potentially cognitively protective activities such as reading, playing games and puzzles, arts and crafts, music engagement and social activities. In these studies, digital activities rated as comparable to or more strongly associated with positive cognitive outcomes than other activities. Why might this be? One possibility is that technology exposures lead to more dynamic cognitive stimulation than analogue exposures<sup>209–211</sup>. For example, both paper-based crossword puzzles and digital word games involve engaging with cognitively complex information (the puzzle), but the digital exposure also involves coping with evolving hardware/software interfaces that change appearance and functioning over time, troubleshooting device or internet connectivity issues and filtering out competing distractions (for example, text messages, advertisements). Such additional layers of cognitive complexity may explain why older adults who were randomized to learn to use computers, tablets, social media, or apps (known as digital inclusion interventions) showed gains in episodic memory, processing speed, or global cognition relative to controls<sup>212–226</sup>. However, not all digital inclusion programmes have observed this pattern<sup>102,171,227–229</sup>, signalling a need for mechanistic studies to better understand the precise processes demanded by different types of technology exposure, which could inform targeted interventions with rigorous matching of control groups.

A second possible pathway by which technology engagement might protect against cognitive decline is by facilitating social connection. Better social connectedness (and its inverse, decreased isolation) is a well-documented correlate of cognitive functioning in older adults<sup>230</sup>. Digital social facilitation was associated with decreased loneliness and depression during the COVID-19 pandemic<sup>30</sup>, heightened feelings of social support and well-being across 6 months in a randomized design<sup>231</sup>, and also direct improvements to cognition<sup>31</sup>. In addition, one study from our systematic review indicated that the cognitive benefits of internet use were strongest in older adults who lived alone<sup>106</sup>. However, the reviewed studies on social media use and cognitive outcomes in older adults showed mixed results (non-significant in pooled analysis), which may reflect that digital social activities can coincide with a decrease in face-to-face social activities<sup>232</sup>. Additional work is therefore needed to understand how, when and for whom digital social connectedness benefits well-being and cognition.

A third possible pathway is that technology use could promote compensatory behaviours, forming a 'digital scaffold'<sup>26</sup> that facilitates better functional outcomes in older adults while general cognitive functioning declines. Digital compensatory behaviours are increasing in older adults<sup>233–235</sup> and have been a focus of interventions to support daily prospective memory tasks such as remembering to pay bills on certain dates or taking medications at set times each day<sup>35</sup>. Digital scaffolding also has implications for understanding clinical diagnoses and disease progression. For example, measurable cognitive impairment is present in both MCI and dementia diagnoses, but a dementia diagnosis is indicated in part when cognitive changes lead to a loss of independence with daily tasks<sup>236</sup>. A testable hypothesis, therefore, is that a technology-enriched environment provides scaffolding to allow individuals with MCI to maintain independence<sup>237</sup> longer for some activities, delaying a diagnostic conversion to dementia or otherwise mitigating the impact of cognitive impairments on everyday functioning<sup>29,238</sup>. As clinical practice continues to move toward an

individualized, precision-medicine approach, it will be necessary for the field to identify for whom and for how long, such digital scaffolding is effective.

While the current meta-analysis showed a consistent, strong positive association between natural uses of digital technologies and overall cognitive well-being, there is no simple answer<sup>239</sup> to whether technology is 'always good' or 'always bad' for the aging brain. For example, moderate screen time might lead to complex and dynamic cognitive stimulation, but excessive passive screen time shows potential for cognitive harm<sup>5,6,21,240</sup>. While number of hours of screen time has not been widely studied in older adults, one study observed a U-shaped association between technology use and cognition in older adults<sup>57</sup>: moderate internet usage was significantly associated with better cognitive outcomes (consistent with the current meta-analysis), but excessive rates of internet usage showed non-significant trends for worse cognitive outcomes (see also refs. 170,183). In addition, digitally enabled social connections improve feelings of loneliness in some older adults<sup>26,105</sup>, but they may also increase exposure to socially driven misinformation<sup>241</sup> or reduce the frequency of face-to-face relationships<sup>242</sup>. Moreover, while digital exposures create opportunities for compensation and digital scaffolding, they can also create new risks for older adults such as digital scams/exploitation<sup>243</sup> and distractions while driving or walking across the road<sup>244</sup>. Therefore, the overall meta-analytic finding should be interpreted to mean that the net effect of the potential costs and benefits has been positive. To this point, we note that the current review focused on 'digital pioneers', that is, the group of middle-aged and older adults who were first exposed to computers, internet and smartphones during adulthood. It is unknown whether the current findings will hold in future decades for people who were initially exposed to digital technologies during childhood or as the types of general digital technology exposure change<sup>5,6,21,245</sup>.

There are limitations to acknowledge to guide future investigations. Although the total number of participants across studies was high ( $N > 400,000$ ), the total number of studies available for OR meta-regression ( $k = 54$ ) provides modest power for moderation analyses. Further, and as noted above, the cross-sectional and longitudinal studies in this literature lend themselves to correlational interpretations, so technology–cognition associations may be explained in part by non-casual factors. At the level of typical individual studies in the literature, digital exposures were often captured by retrospective recall (which limits understanding of use patterns<sup>246,247</sup>) and without information on the date when the computer, internet, or smartphone devices began to be used (which limits understanding of how much digital exposure is needed to produce cognitive benefits). Some cognitive reserve proxies have also not been widely studied in the technology–cognition literature ( $\leq 5$  studies), such as general intelligence<sup>3</sup>, interest in acquiring new complex skills and type of occupation<sup>248–250</sup>.

It is also important to point out that the majority of the studies were from moderate to high-income countries. Particular attention should be paid to studies of technology trends in lower-middle and low-income countries<sup>39</sup>, which are expected to show the largest increase in dementia incidence in the coming years<sup>251</sup> but are also predicted to have a rapid expansion of technological infrastructure driven by mobile technologies<sup>252</sup>. If accessing new technologies is too difficult or too costly for older adults, then such digital expansion is likely to perpetuate or accentuate digital health disparities<sup>253</sup>.

In closing, the generation that brought the digital revolution to the world is now reaching the age where neurodegenerative disease and cognitive decline emerge. The data from 411,430 digital pioneers indicated that natural uses of digital technology were associated with better cognitive outcomes, consistent with the viewpoint that technology exposures facilitate behaviours and mental processes that contribute to reserve. Theoretical and applied questions remain, with the state of the field indicating the need to consider complex interactions between aging, neurocognitive processes and types of digital exposure. With

greater mechanistic understanding of these interactions, clinicians, researchers and engineers can help guide future generations of older adults in using emerging technologies in a manner that optimizes cognitive outcomes and minimizes harms, as was generally observed for the digital pioneers.

## Methods

### Literature search and selection criteria

Systematic review and meta-analysis of the literature were conducted in accordance with the 2020 PRISMA statement<sup>254</sup>. Medline through PubMed, PsycInfo, CINAHL, Scopus, Cochrane Library and Web of Science databases were searched through June 2024 for the following search terms: ('older adults' OR aging OR 'mild cognitive impairment' OR dementia) AND (Computer OR smartphone OR internet OR email) AND (cognition OR cognitive) AND (prevention OR protection OR risk). ProQuest and Science Direct databases were also searched through June 2024 using the terms 'Cognition' AND ('older adults' OR dementia) AND (computer use OR smartphone use OR internet use) AND (prevention OR risk). When possible, database search results were limited to peer-reviewed, research article, or journal article types (CINAHL, Science Direct, Scopus, Web of Science, ProQuest), articles published in English (Science Direct, Scopus, ProQuest) and articles published with middle-aged or older adult groups (PsycInfo, CINAHL). An initial search and screening was conducted using Excel in June 2023; an updated search and screening in July 2024 used Covidence to remove duplicates across databases. Screening was conducted in two phases: title/abstract screening and full-text screening, by two independent reviewers who met to discuss and resolve differences at each stage, specifically with respect to the search inclusion/exclusion criteria. In the few cases of continued disagreement during title/abstract screening ( $<1\%$ ), the title/abstract was included in the full-text review; there were no unresolved disagreements at the full-text review stage after discussion. During full-text review, additional studies were identified through backward and forward citation tracking.

Inclusion criteria included (1) an observational or cohort study design (digital-based interventions were excluded to focus on natural uses of digital technology); (2) an objective cognitive measure or diagnosis outcome (MCI or dementia); (3) identification of a digital technology use as an 'independent variable', defined as general computer, smartphone, internet, social media or mixed/multiple uses (in contrast to specific app use, video game or 'brain game' use, examples of which are reviewed elsewhere<sup>255,256</sup>); (4) separate reporting of the technology variable from household technologies such as micro-waves, sedentary/leisure activity variables and other cognitive reserve measures (rather than being reported only as a composite); (5) the technology variable reflecting digital device usage rather than anxiety/technophobia scales; (6) the sample (or a subsample) consisting of adults aged  $\geq 50$  years old at baseline; (7) the study being published in a peer-reviewed journal (excluding dissertations and theses); and (8) availability of an English language record for review.

Initial analysis of studies that met inclusion criteria indicated that many research reports were derived from the same parent studies; only one cross-sectional and one longitudinal study per parent-study database were selected for the main analysis, except for cases in which the papers reported on distinct technology exposures that were included in the parent study. Further, there was significant heterogeneity in the statistical methods employed to analyse technology use data, although the majority clustered into ORs or HRs. Studies that did not report or allow sufficient information to derive an OR or HR are described in Supplementary Table 1.

### Data extraction and study quality evaluation

Data extraction and quality ratings were performed independently by the two study authors who met to discuss and resolve any inconsistencies (10.01% of entries). Study quality ratings were systematically

evaluated with a modified version of the NHLBI study quality observational and cohort cross-sectional quality assessment tool<sup>257</sup>. Each study was rated on clearly stating the research objectives, defining the study population, recruiting from the same population and applying inclusion/exclusion criteria equally, measuring the exposure of interest (technology) before the outcome (cognition), examining different levels or categories of technology usage (if corresponding analyses were reported), defining technology usage clearly and consistently for all participants, defining cognitive-outcome measures clearly and consistently across all participants, blinding/masking the cognitive-outcome assessors to technology usage and controlling for potential confounding variables. For longitudinal designs, we also rated whether the study assessed/reported technology usage more than once over time and if attrition was minimized to <20% at follow-up. We did not include ratings for the NHLBI items on participation rate of eligible persons, choosing instead to evaluate sampling methodology of probability sampling versus non-random convenience samples. We also did not include ratings of having a sufficient timeframe to expect to see an association because studies in this literature questioned participants about current digital usage rather than the timeframe in which they began using the digital technology. Each item was rated as yes, no, cannot determine or not applicable, and study quality ratings were the proportion of 'yes' responses (accounting for denominator differences when removing items that were not applicable to a given study).

In addition to the systematic study quality ratings, the authors independently extracted information on several study features that might influence outcomes. These variables included sample size, baseline age, gender (percent female), longitudinal duration, type of technology studied, whether baseline cognition/cognitive status was controlled for, and type of cognitive outcome (diagnosis versus cognitive scale). We used Scimago journal rankings to extract information on where studies in this literature were published (Supplementary Fig. 2). To characterize the context in which the study was performed, we extracted data on the income level of the country where the study was conducted following World Bank definitions of upper income, upper-middle income, lower-middle income or low income; the year that data collection began; and if all study methods were face to face with paper and pencil (versus online or participating on a tablet/computer). We also recorded whether each reported/derived outcome controlled for known proxies of socioeconomic status (for example, household income), cognitive reserve (education, other cognitive leisure activities, baseline cognition, exercise/physical activity), health (smoking, drinking, depression, mobility status, medical co-morbidities, body mass index and self-rated health) and social support (social support indices, marital status and living alone status).

### Data analysis

Individual studies in this literature have employed several different statistical methodologies for their primary analyses (that is, ORs, HRs, path analyses, regression analyses, correlational analyses and so on). To maximize the inclusion of studies for our meta-analysis, we used the following methodology for estimating effect size. First, whenever reported, we extracted the odds ratio values that were maximally adjusted for covariates. If an adjusted OR was not available, information from the study report was used to derive an unadjusted OR from other effect size measures; these are described as derived OR throughout Supplementary Table 2. All ORs were also converted such that higher ORs (>1.0) indicated that technology usage was associated with increased risk for cognitive decline and lower ORs (<1.0) indicated that technology usage was associated with protection against cognitive decline.

Seven studies reported their primary outcomes as covariate-adjusted hazard ratios. HR and OR statistical approaches differ fundamentally: ORs focus on associations between two variables over the course of the study period, while HRs focus on time-dependent rates

in a longitudinal study<sup>258</sup>. Therefore, HR values cannot be directly combined with OR values in meta-analyses or meta-regressions (for example, HR = 0.80 is not the same effect size interpretation as OR = 0.80; ref. 259). In our review, 7 studies reported HR as their primary outcome, but four of these studies also reported sufficient information to derive an OR. Therefore, we reported two top line analyses: one analysis for ORs which included 54 of the 57 studies meeting inclusion criteria and a second analysis for HRs that included all 7 of the adjusted HR findings. Because seven studies would be too small for conducting a meta-regression, we limited meta-regressions to the OR values.

For studies with multiple cognitive endpoints or subgroups of technology use, outcomes were pooled for the primary analysis. Effect size direction was reversed for non-diagnostic cognitive-outcome measures in which higher scores indicated better cognition so as to align with the direction of diagnostic variables (lower dementia rates indicated better cognition). If a study reported effect sizes specifically for a middle-to-older-aged sample (any group with mean age of 50 or higher), that effect was entered into the analysis. Notes on transformations of effect sizes for included studies are described in Supplementary Table 2. Overall effect sizes were weighted by the inverse of each study's variance.

To test the role of moderators on effect sizes, three meta-regressions were undertaken to evaluate the impact of sample characteristics, study characteristics and conceptual factors. Sample characteristics included average age at baseline, percentage female, sample size and income level of the country where the study was conducted. Study characteristics included use of a cross-sectional versus longitudinal study design, the year data collection began, NHLBI study quality ratings, type of outcome (cognitive versus diagnosis) and whether data collection was solely face to face with pencil and paper or required the use of digital technology. Conceptual factors included dichotomous variables for whether each study's reported or derived effect size adjusted for socioeconomic status proxies, cognitive reserve proxies, health factors and social support factors. These variables were regressed on the reported/derived ORs to determine whether the presence of such adjustments moderated the observed effect size. All analyses were two-tailed tests and were conducted using the Comprehensive Meta Analysis v.4 software<sup>260,261</sup>.

### Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

### Data availability

The review was not registered in PROSPERO but raw data extracted from publications as well as processed effect sizes are available at the Open Science Framework (<https://osf.io/av6nu/>).

### Code availability

Analyses were conducted with Comprehensive Meta-Analysis Software with data files available; no custom code was utilized.

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## Author contributions

Both authors confirm equal contribution. J.F.B. and M.K.S. were responsible for study conception and design, data extraction, analysis and interpretation of results, and paper preparation.

## Competing interests

The authors declare no competing interests.

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